



Partitioning and Relationship Detection for Large-Scale Semantic Graphs

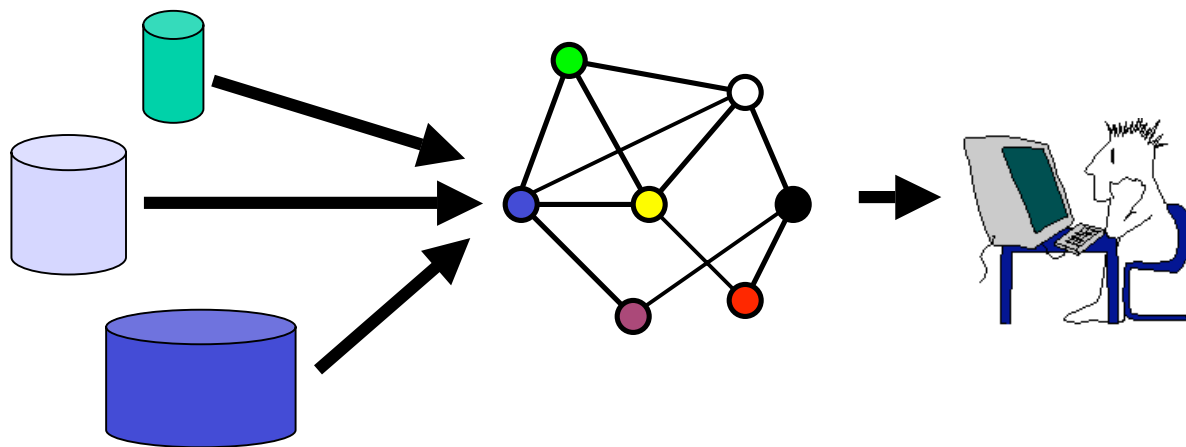
DHS Advanced Scientific Computing Program

Edmond Chow

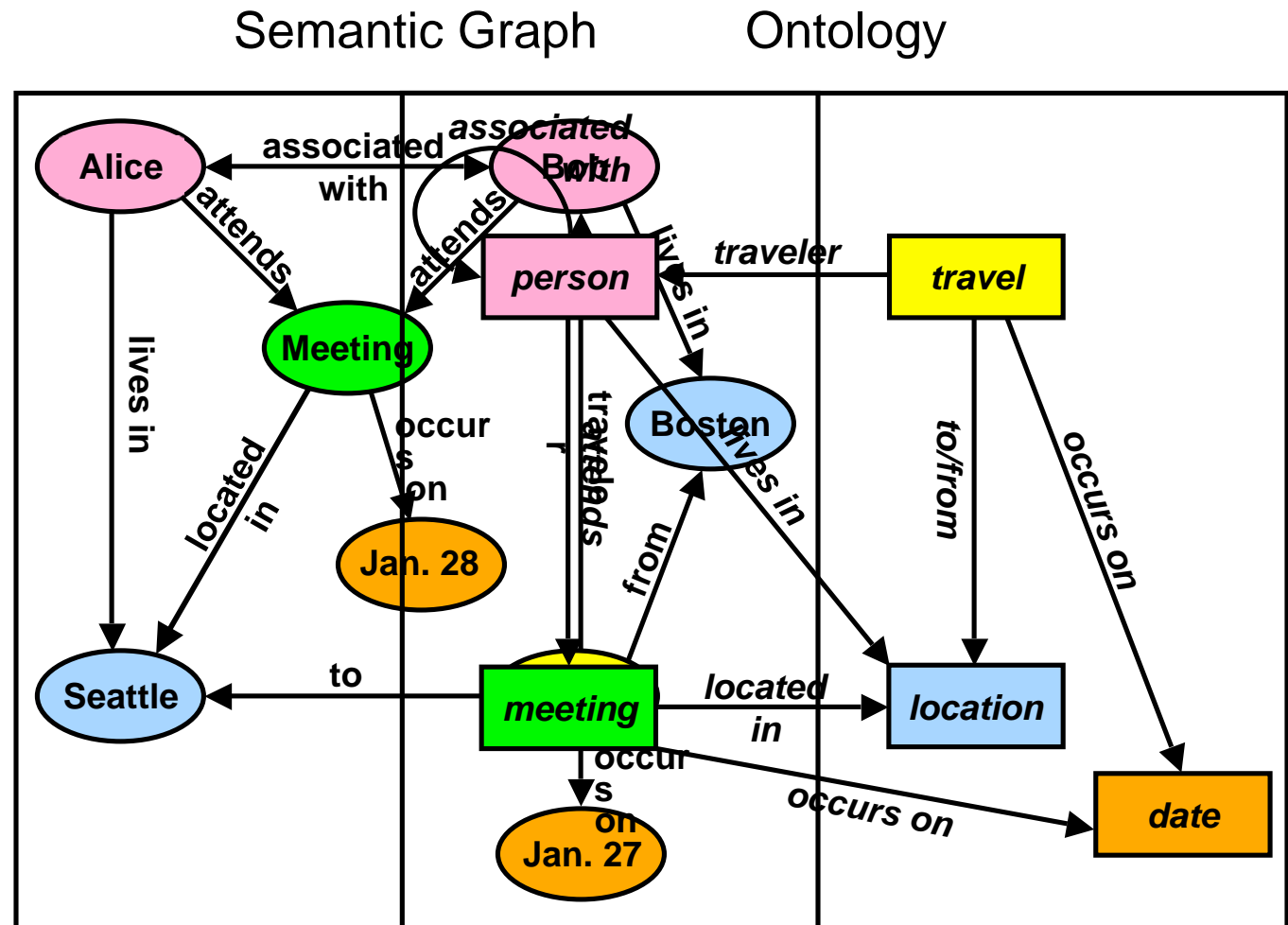
Lawrence Livermore National Laboratory

Motivation

- Intelligence analysts must identify relationships in huge amounts of data
- Data is collected from multiple sources at increasing rates
- Challenge: identify relationships and uncover patterns in a timely manner
- Approach: use *semantic graphs* to represent the data and graph algorithms to discover hidden relationships



Semantic graphs have attributes and types on the vertices and edges

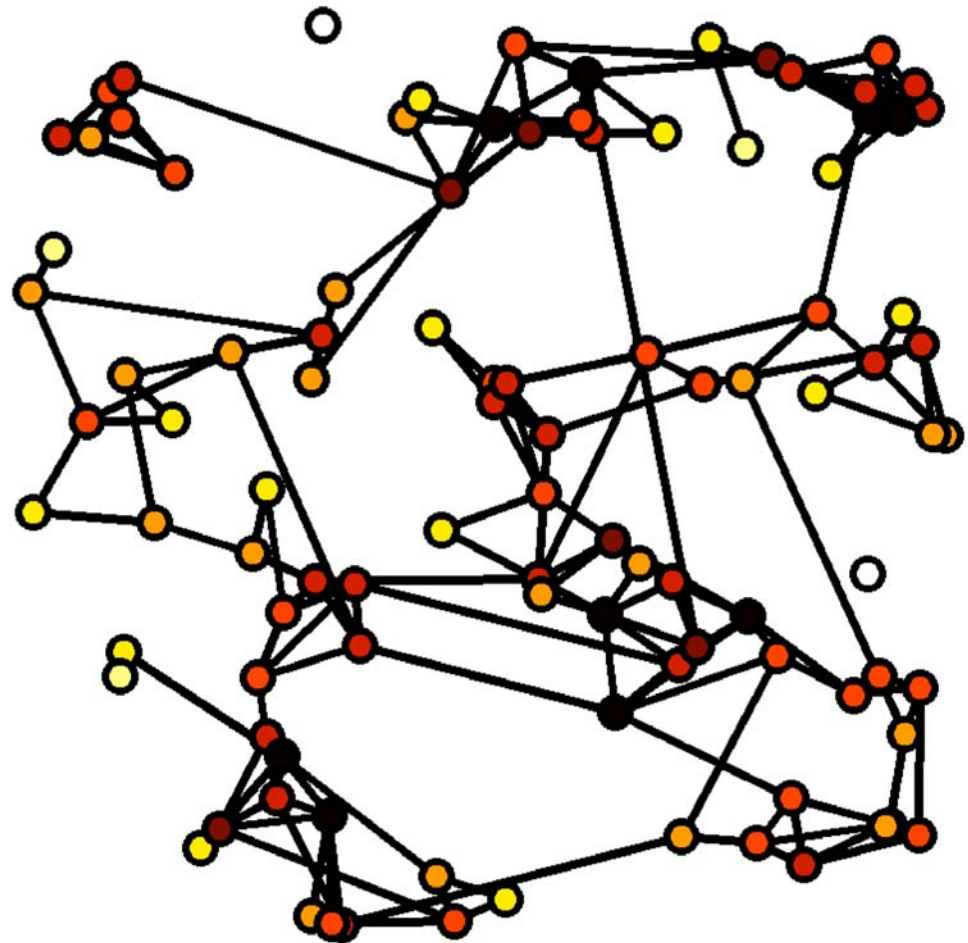


Semantic graphs for information analysis are becoming enormous

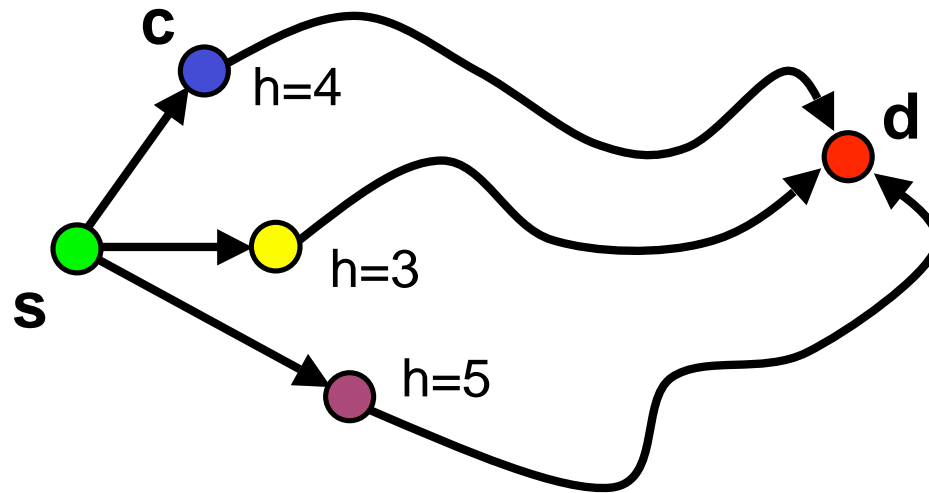
- Distributed memory parallel computers must be used to store and search these graphs
- Graphs must be partitioned onto separate memories and graph searches must have low communication cost
- Topological properties of semantic graphs make standard partitioning techniques ineffective
- Our goals are to develop partitioners and efficient, scalable parallel search algorithms

We are developing parallel algorithms to search massive graphs

- Partitioning for semantic graphs
- Heuristics for searching semantic graphs, incl. template matching
- Scalable parallel implementations
- Properties of complex information networks
- Knowledge discovery in relational data



To find the shortest path, use A* search,
which uses a heuristic to guide the search

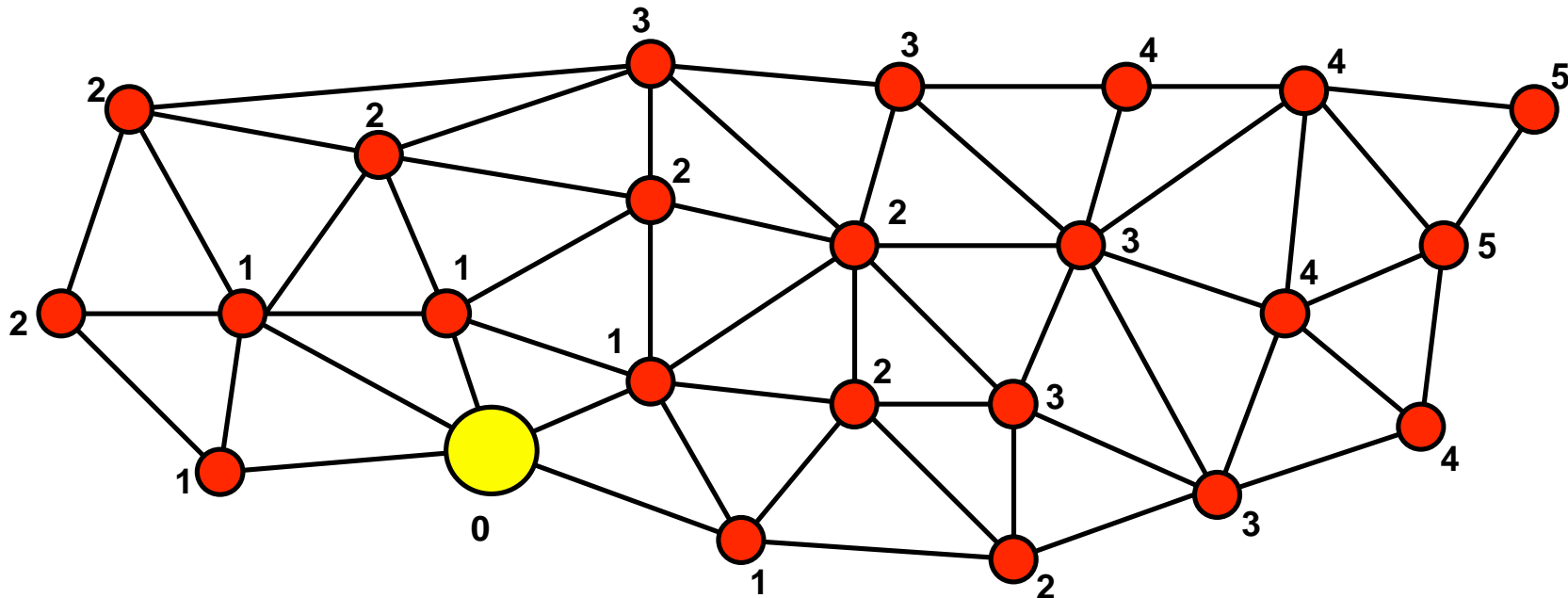


Use a cost function of the form:

$$f(s,c,d) = g(s,c) + h(c,d)$$

h is *admissible* if it never over-estimates actual cost

Level-difference heuristic

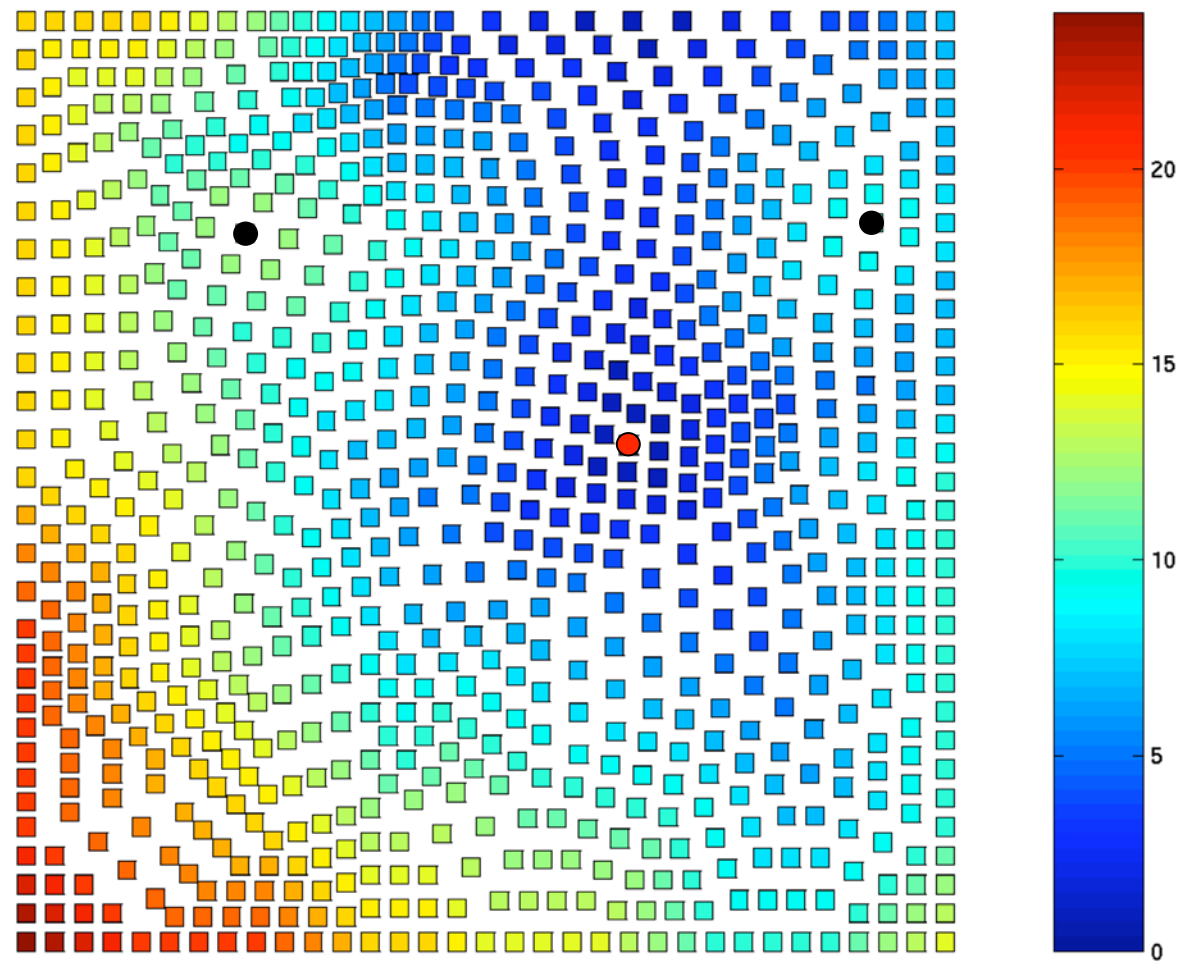


$$h_1(i,j) = | \text{level}(i) - \text{level}(j) |$$

$$h(i,j) = \max\{ h_1(i,j), \dots, h_m(i,j) \}, \quad m \text{ centers}$$

Error in the heuristic can be bounded

Example: heuristic distance to a vertex on a mesh

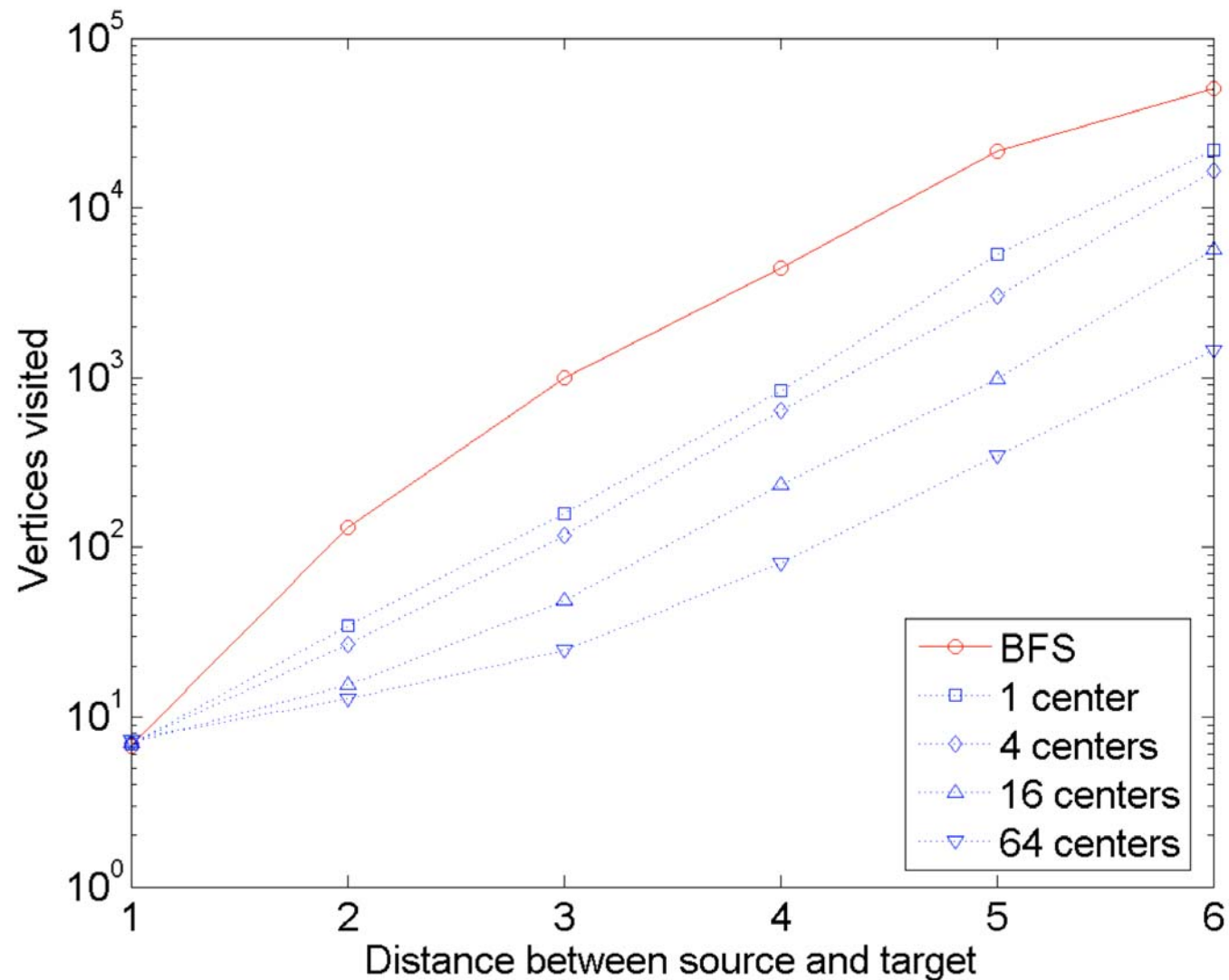


Heuristic distance to red vertex given two center vertices

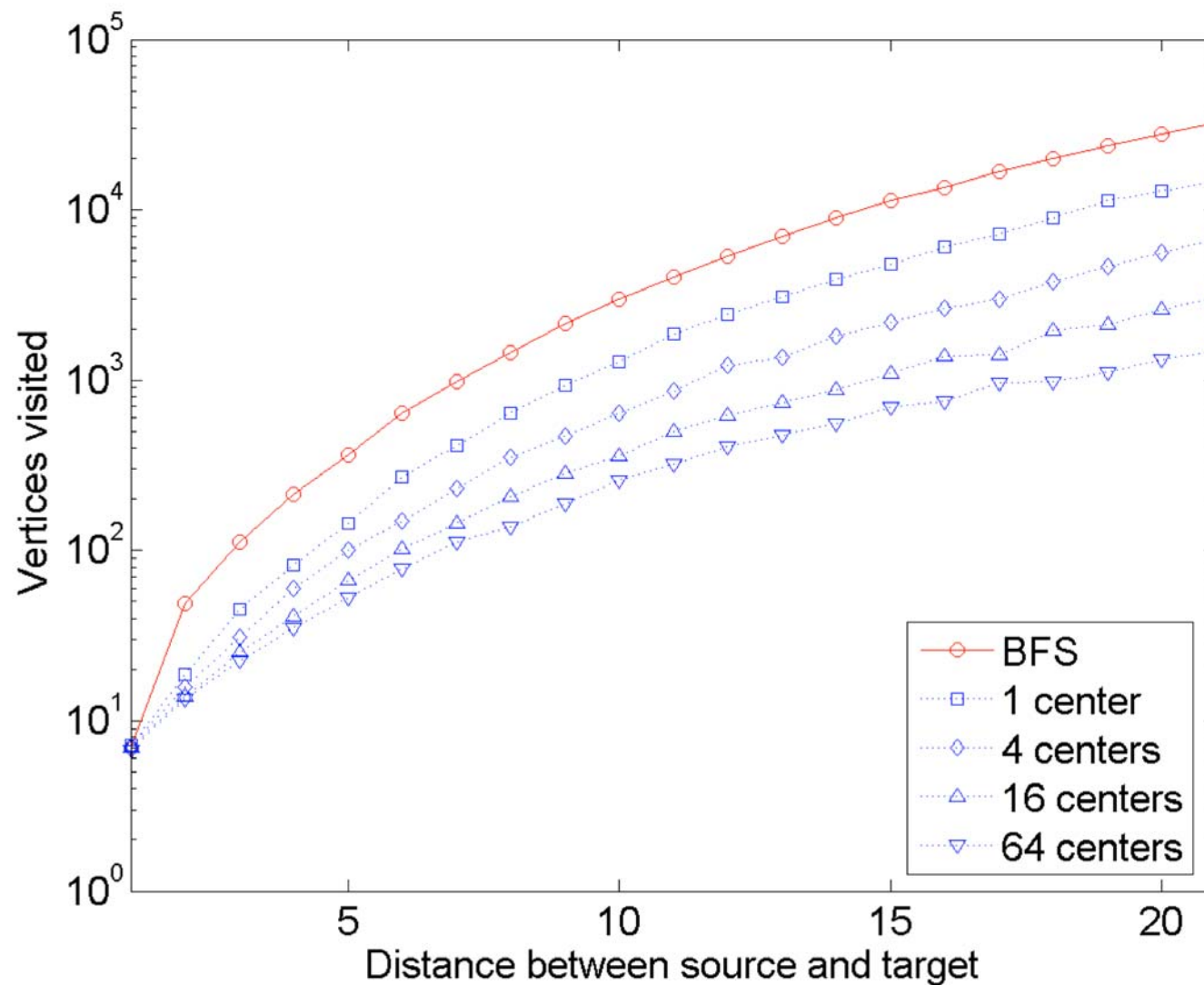
Test graphs

| <i>Type</i> | <i>Vertices</i> | <i>Edges</i> | <i>Ave Deg</i> | <i>Ave Path Length</i> | <i>Diameter</i> |
|-------------|-----------------|--------------|----------------|------------------------|-----------------|
| Random | 63848 | 191999 | 6.0 | 6.4 | 12 |
| Random | 51065 | 61415 | 2.4 | 15.0 | 39 |
| Random | 127664 | 383997 | 6.0 | 6.8 | 12 |
| Spatial | 64000 | 192000 | 6.0 | 21.3 | 39 |
| Mesh | 64304 | 192043 | 6.0 | 116.4 | 278 |
| Internet | 112969 | 181639 | 3.2 | 9.9 | 27 |

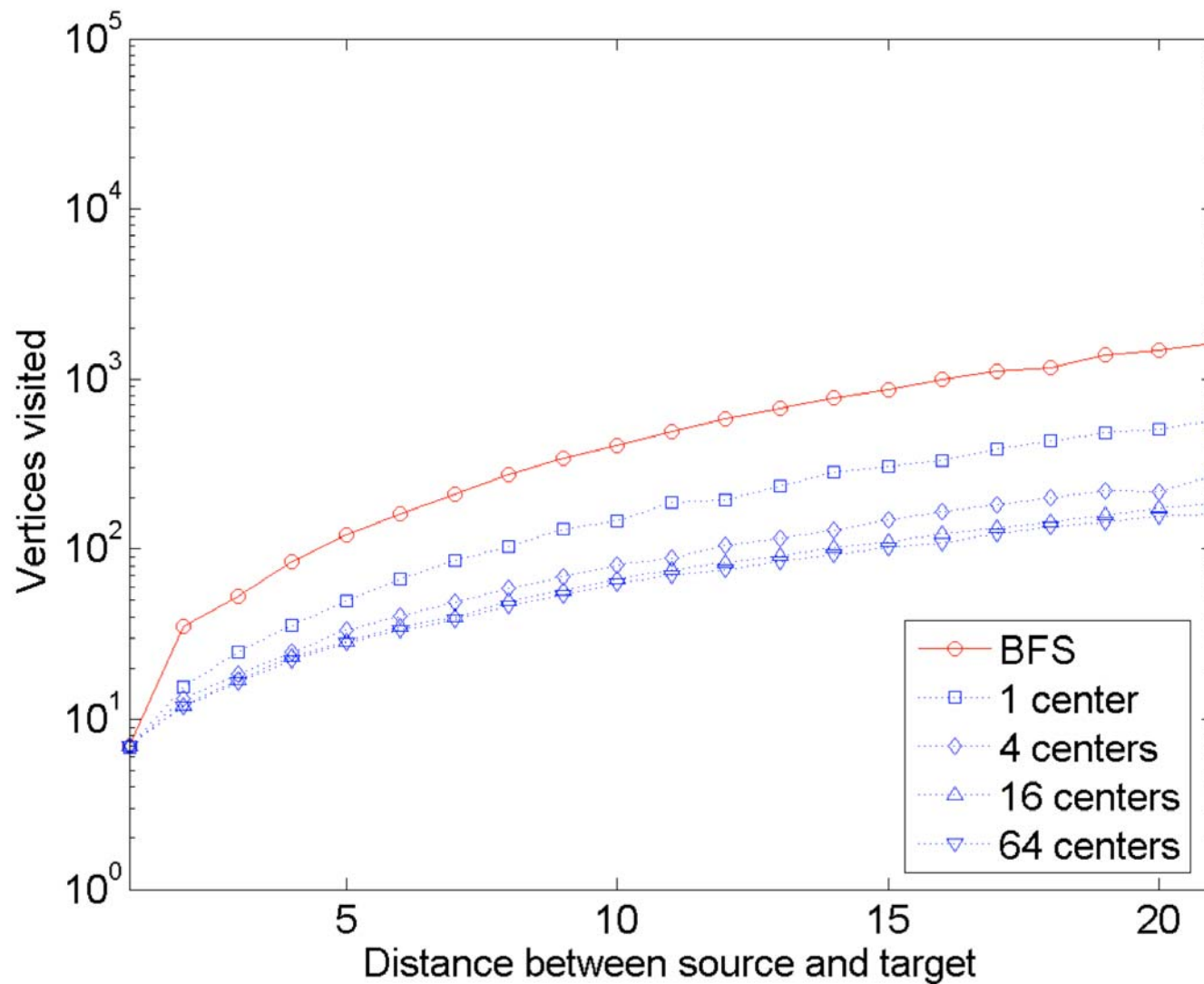
Random graph, 64k vertices, $\langle k \rangle = 6$



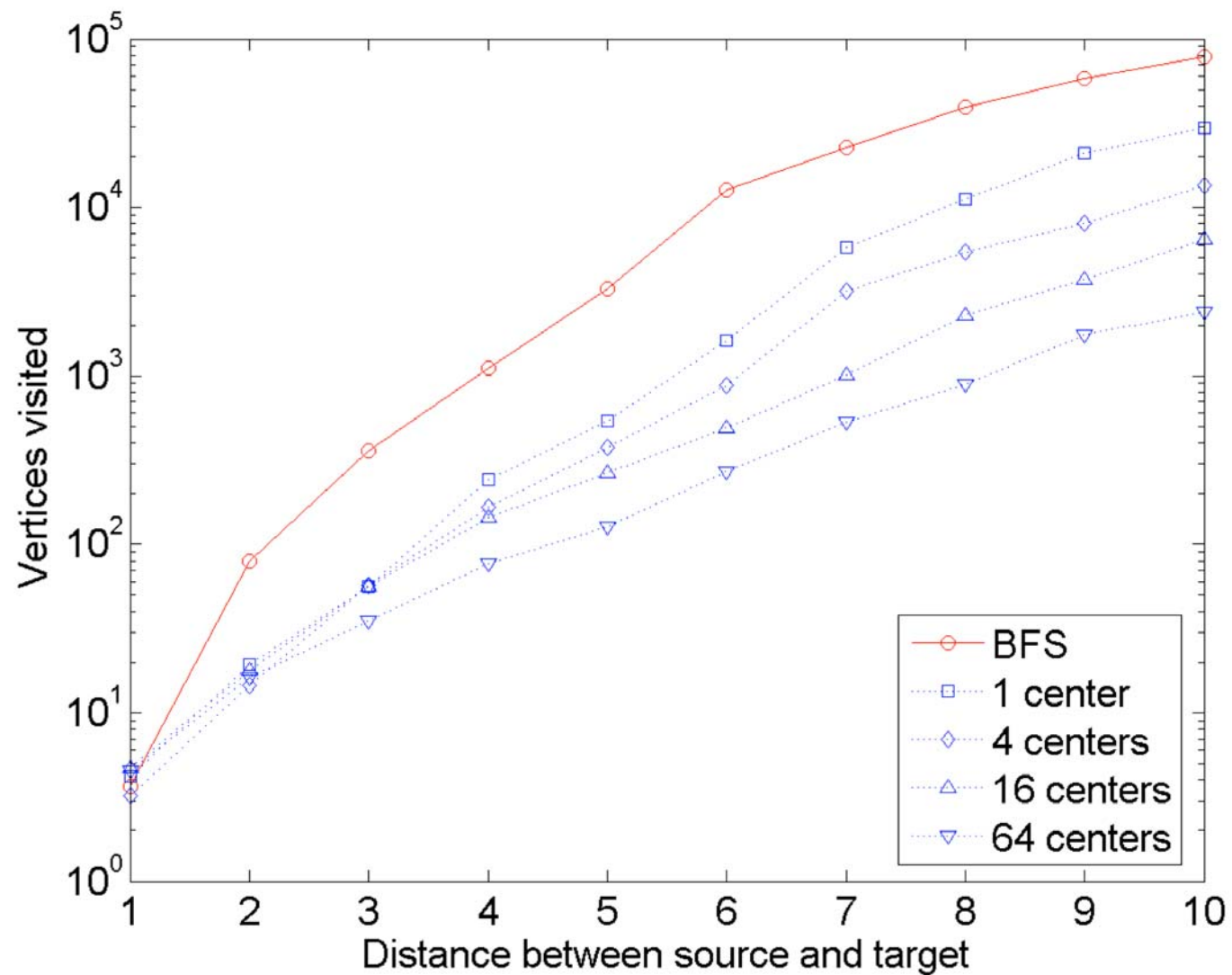
Spatial graph, 64k vertices, $\alpha=4$



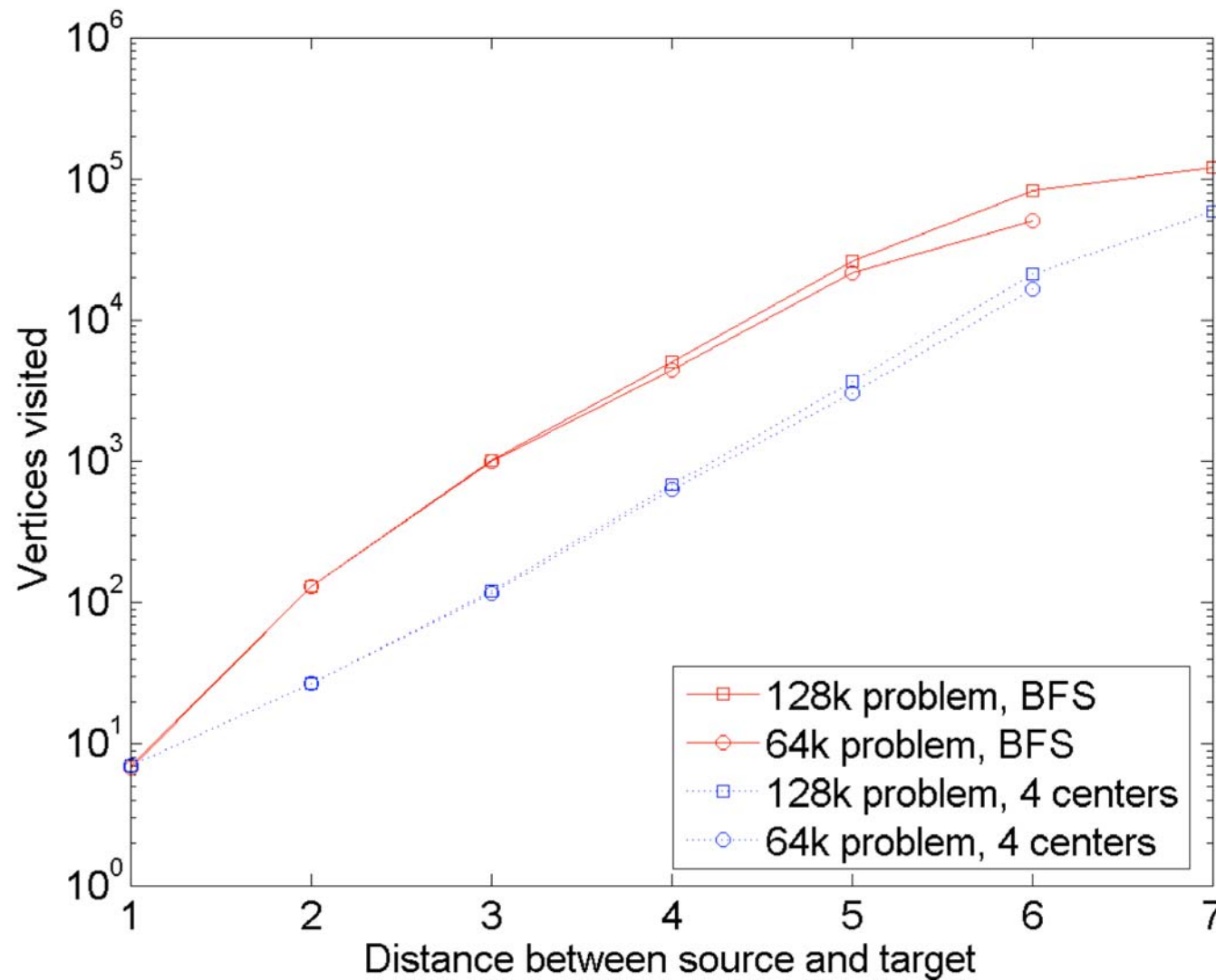
2-D Mesh, 64k vertices



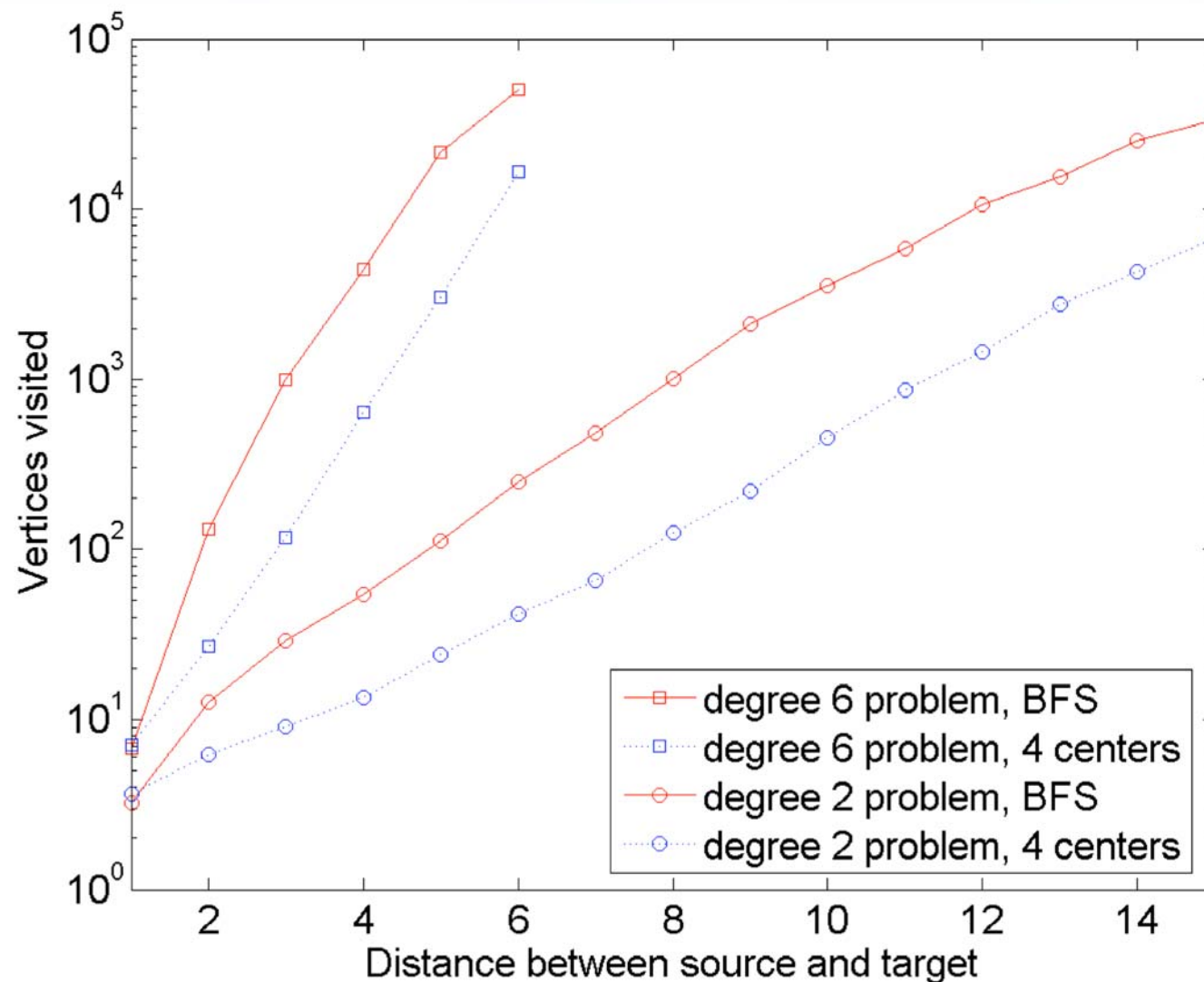
Internet graph



Scalability (random graphs $\langle k \rangle = 6$)



Effect of vertex degree (random graphs)

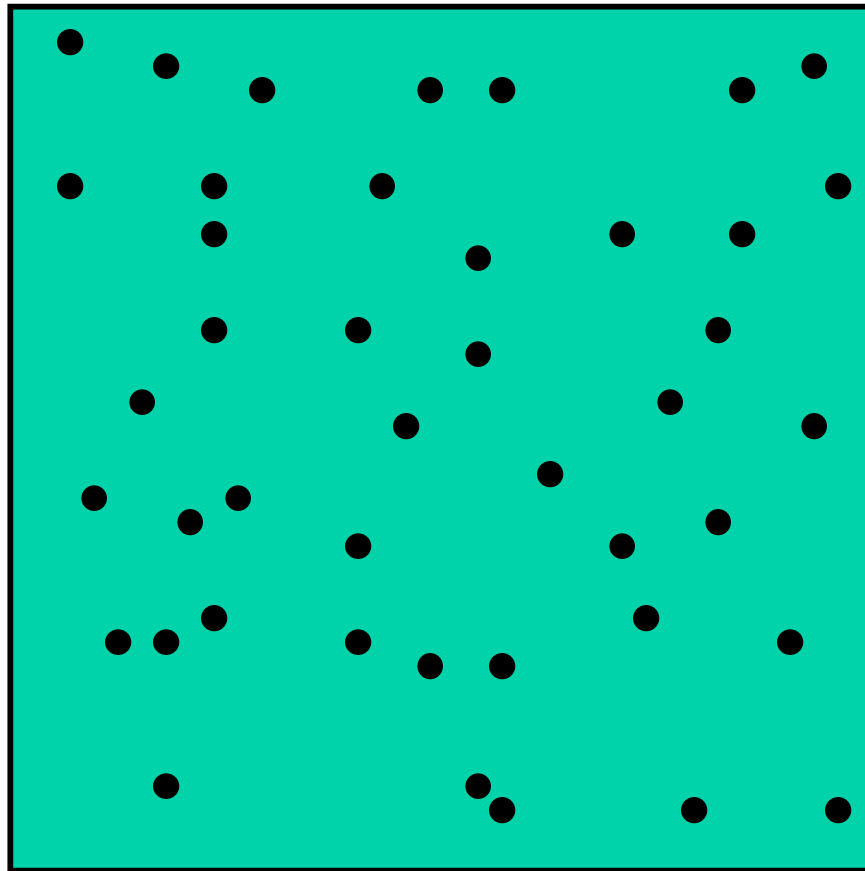




2D Partitioning

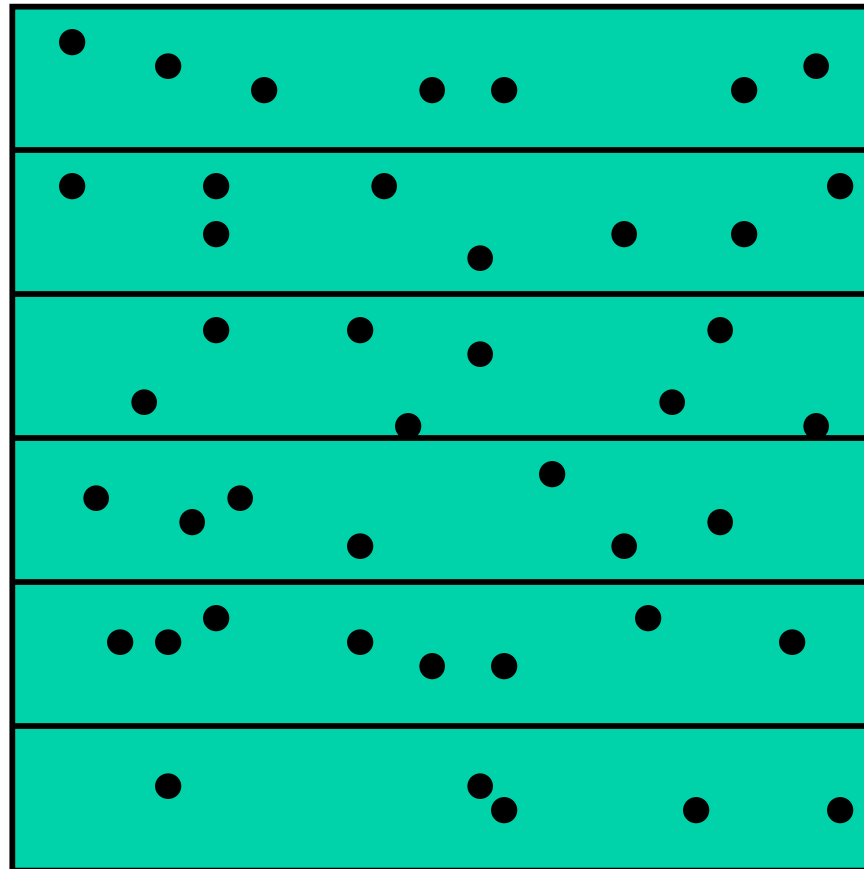
- Partition the vertices (1D) or the edges (2D)
- 2D partitioning has been advocated for sparse matrices where the sparsity pattern is difficult to exploit (Hendrickson, Leland, and Plimpton 1995)
- Many variants of 2D partitioning (Catalyurek 1999)
- 2D checkerboard variant is perhaps most useful
 - Redistribution-free, transpose-free doubling/halving (Lewis and van de Geijn 1993, Lewis, Payne, and van de Geijn 1994)
 - 2D checkerboard (Catalyurek 1999, Catalyurek and Aykanat 2001)

Example: Adjacency matrix

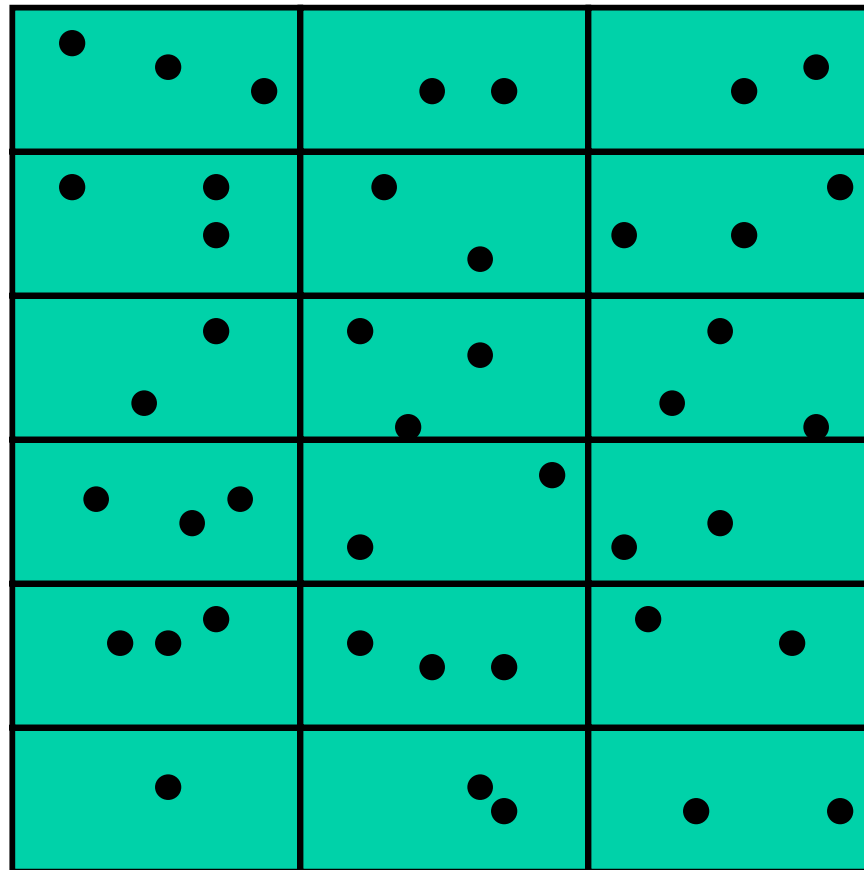


Partition to
minimize
processor
communication
while maintaining
load balance

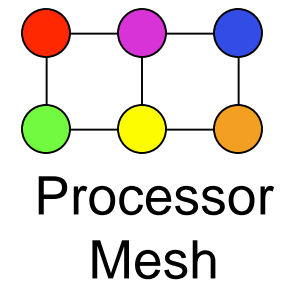
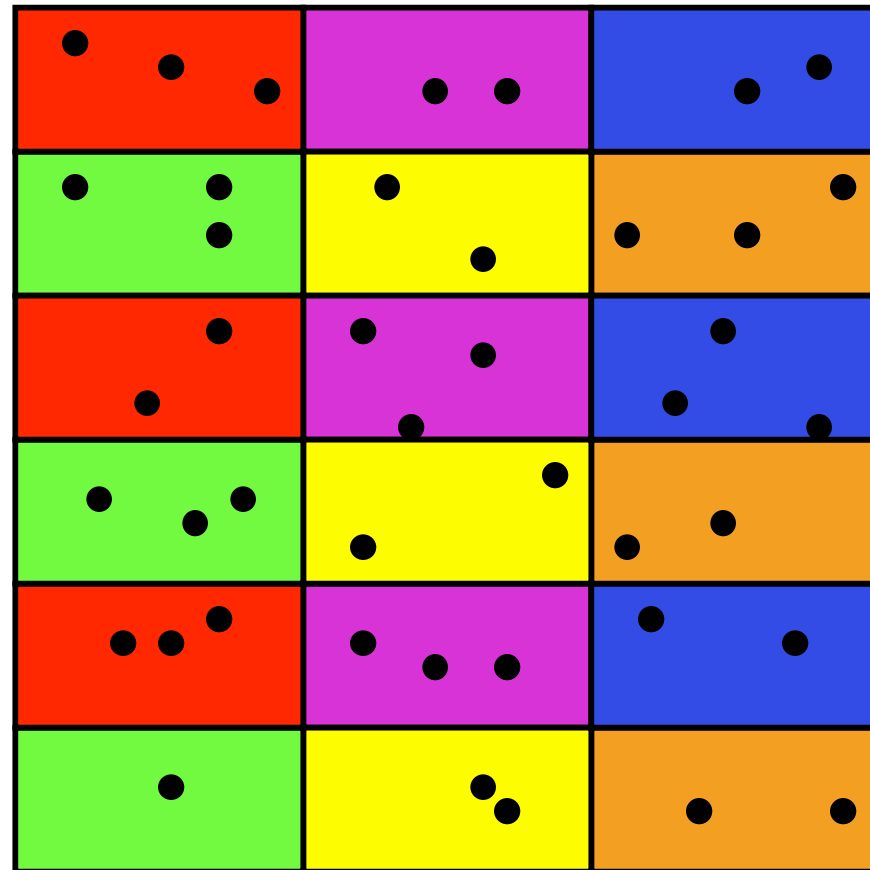
Example: 6-way Vertex Partitioning



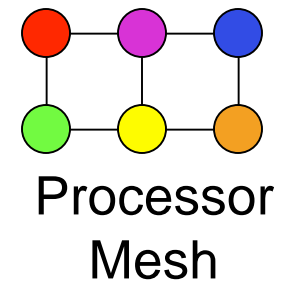
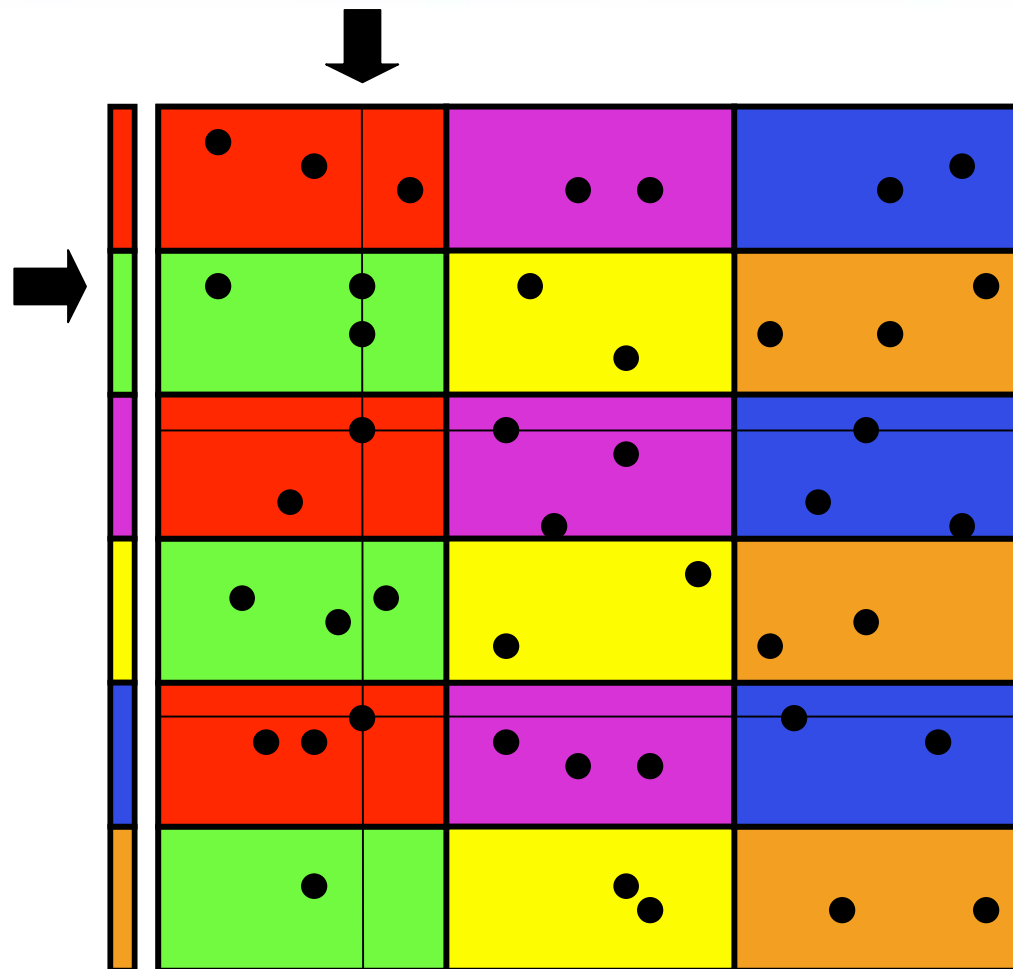
Example: 2x3 Edge Partitioning



Example: 2x3 Edge Partitioning



Example: 2x3 Edge Partitioning



Level-synchronized Parallel Search

Do $l=0$ to ... until target is found

F = set of assigned vertices with level l

Column Expand communication (send F , receive F')

N = set of neighbor vertices of F'

Row Fold communication (send N , receive N')

Update levels of vertices in N'

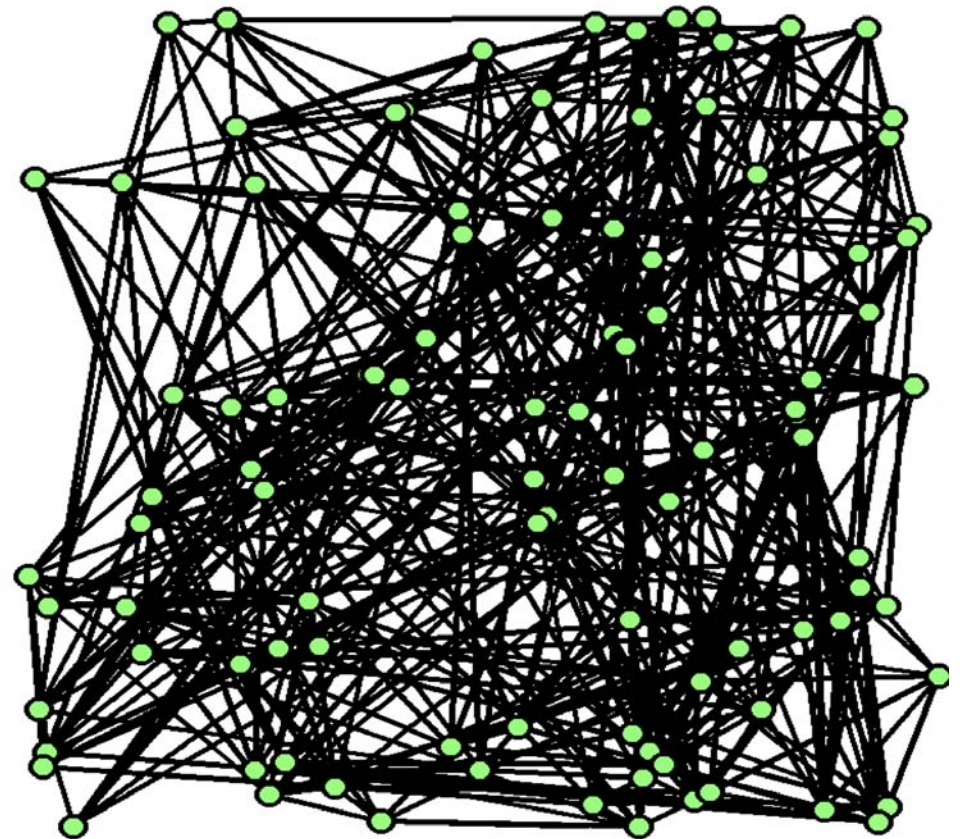
Enddo

- Expand is all-gather or all-to-all
- Reduce is all-to-all or reduce-scatter
- Must store *vertex* lists in sparse mode
- Storage is scalable for random graphs
- If the blocks are balanced, then the communication is balanced for any graph

Spatial networks

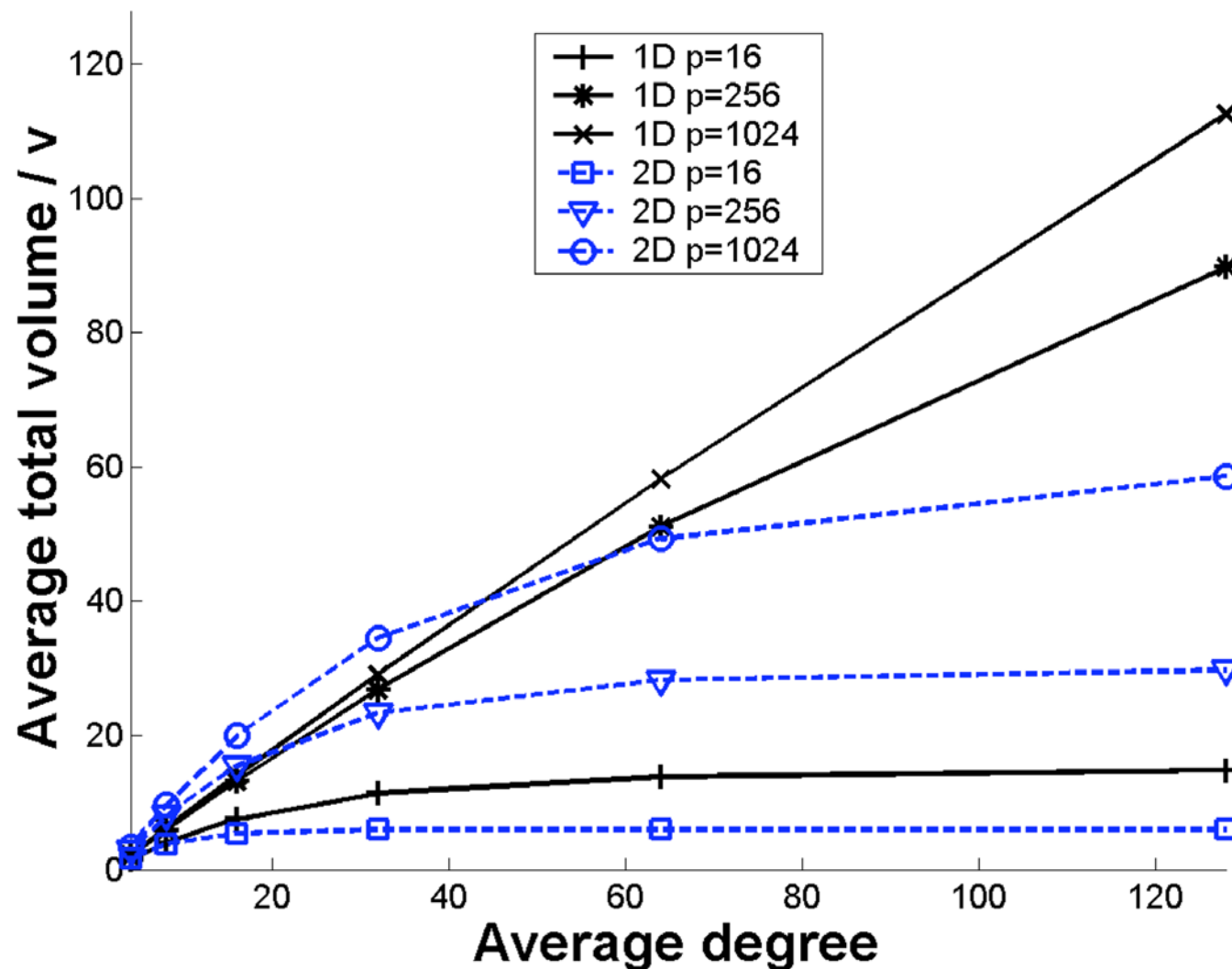
- $P(\text{edge}) \sim \text{length}(\text{edge})^{-\alpha}$
- Poisson random graphs have $\alpha = 0$
- α is related to clustering coefficient
- Best partitioning is geometric

Spatial network with $\alpha = 1$
and avg. degree 10



Communication volume for 1D and 2D partitioning

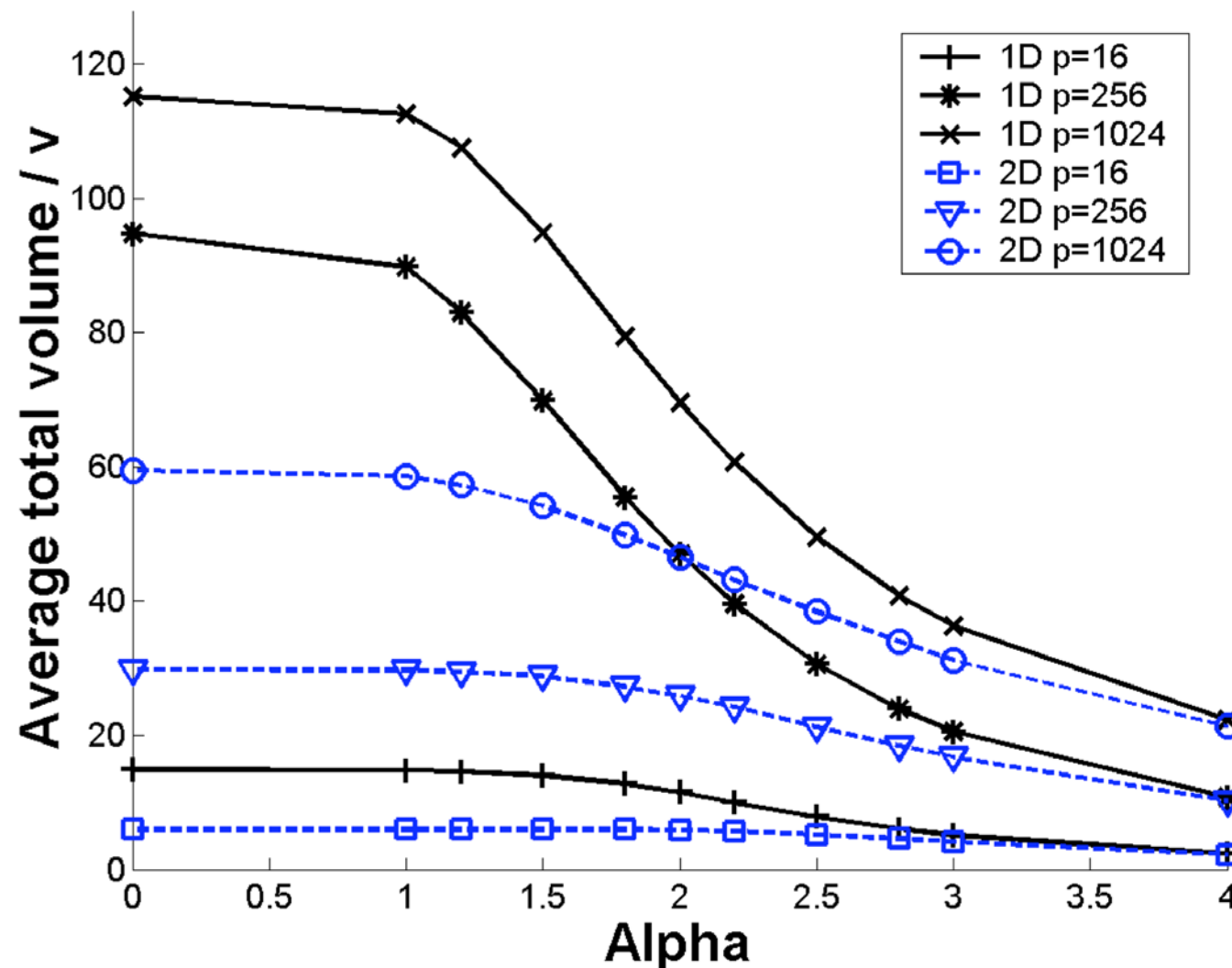
Alpha = 1



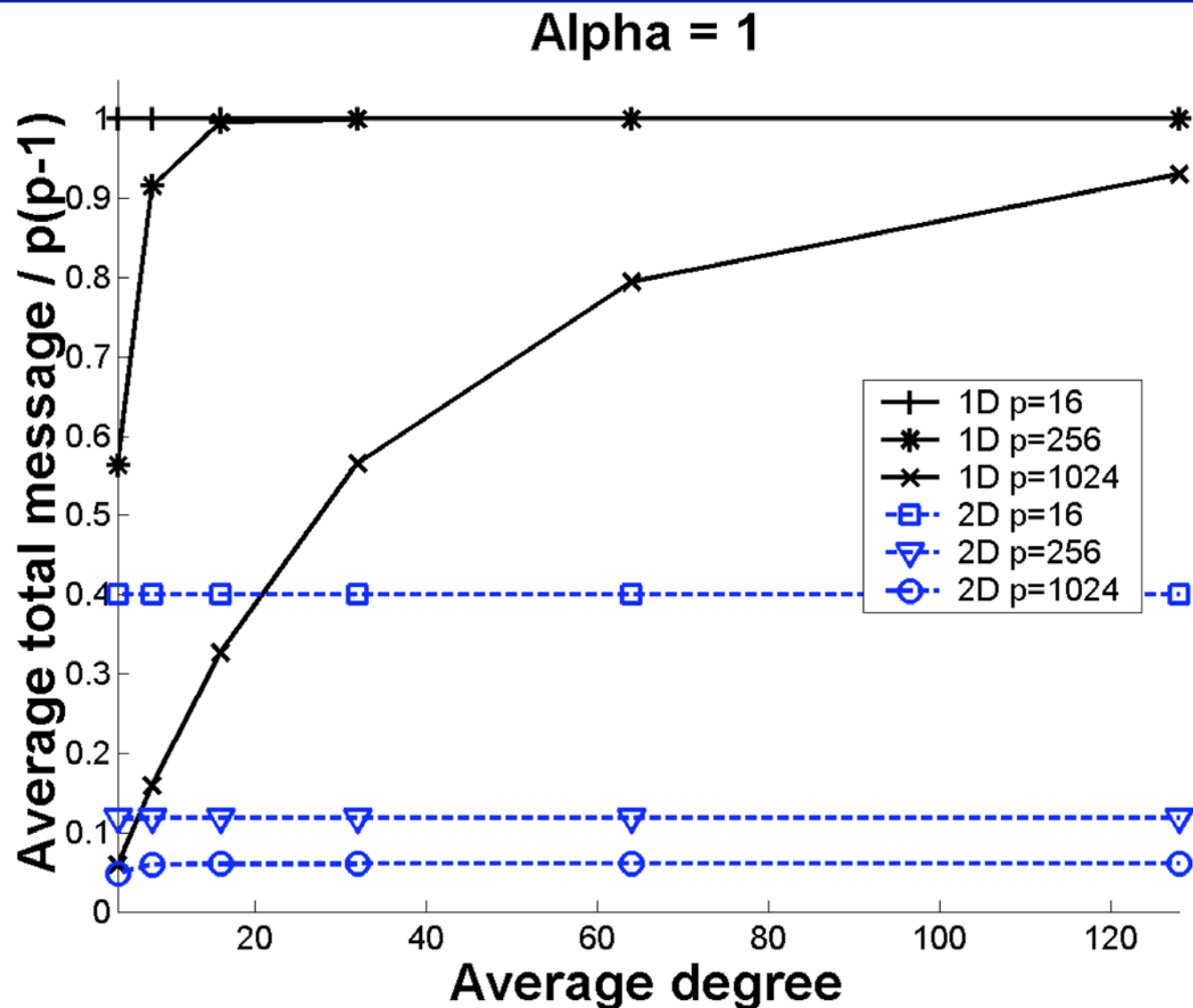
Computed
by PaToH

Communication volume for 1D and 2D partitioning

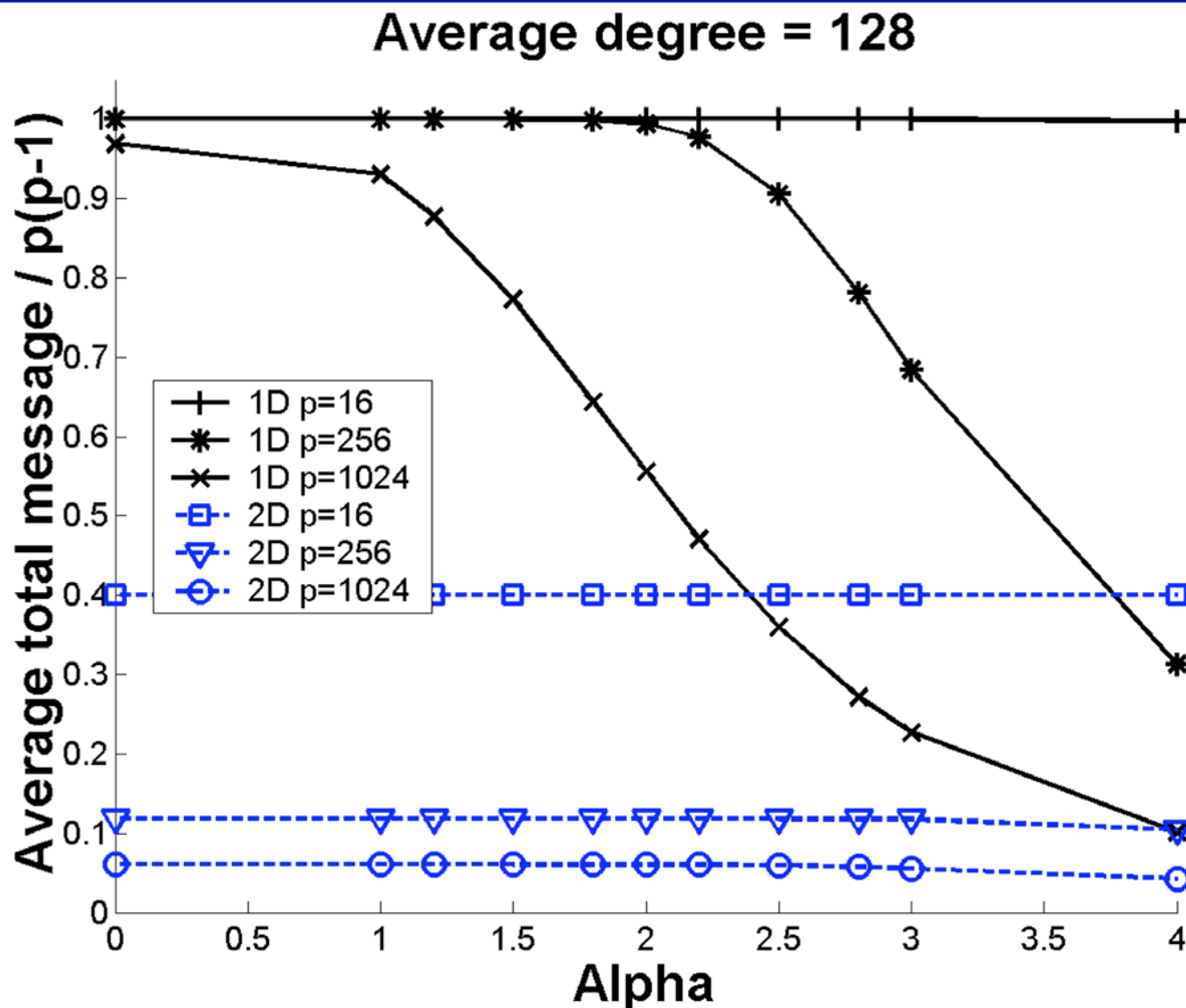
Average degree = 128



Number of messages for 1D and 2D partitioning



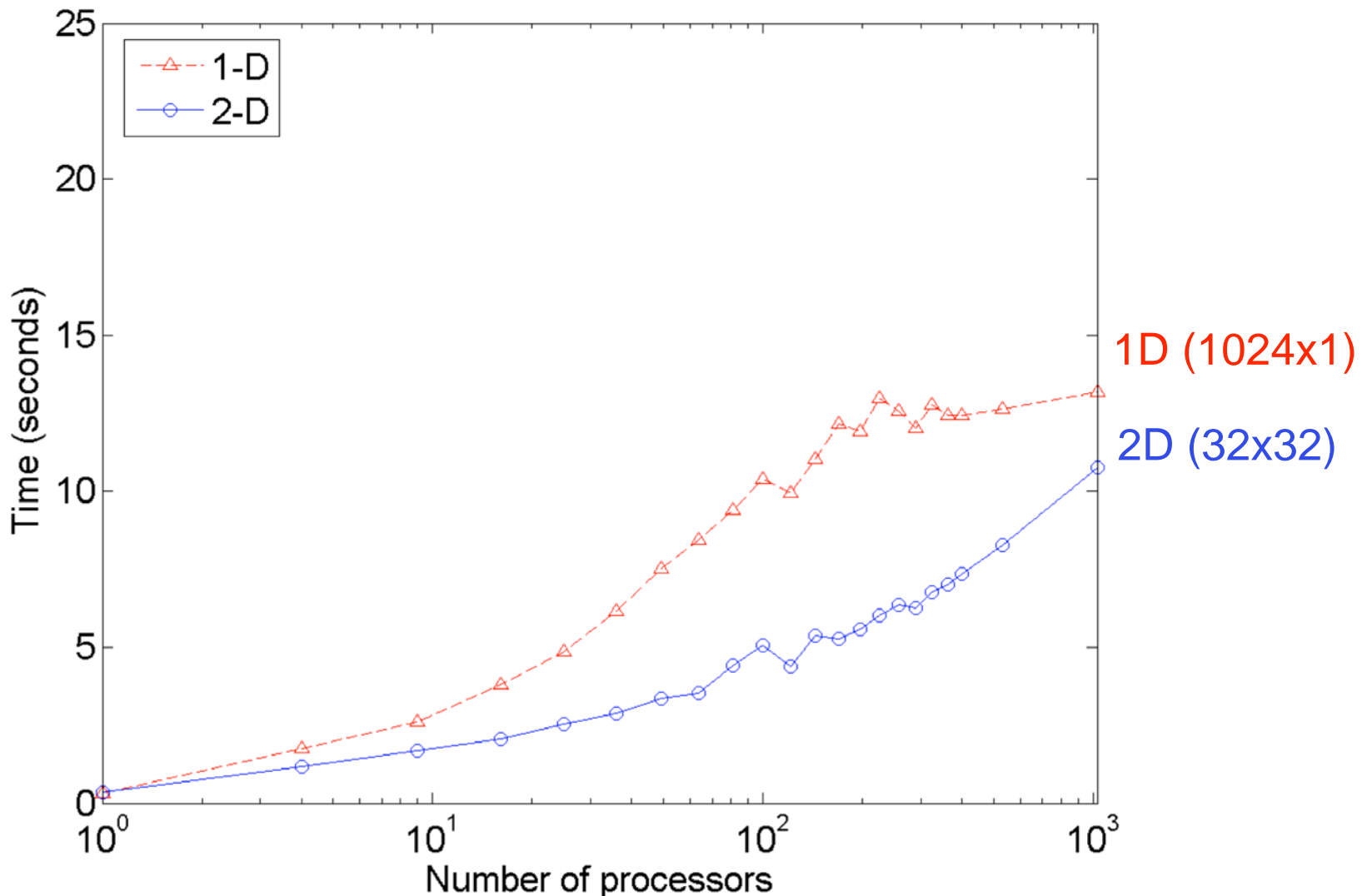
Number of messages for 1D and 2D partitioning



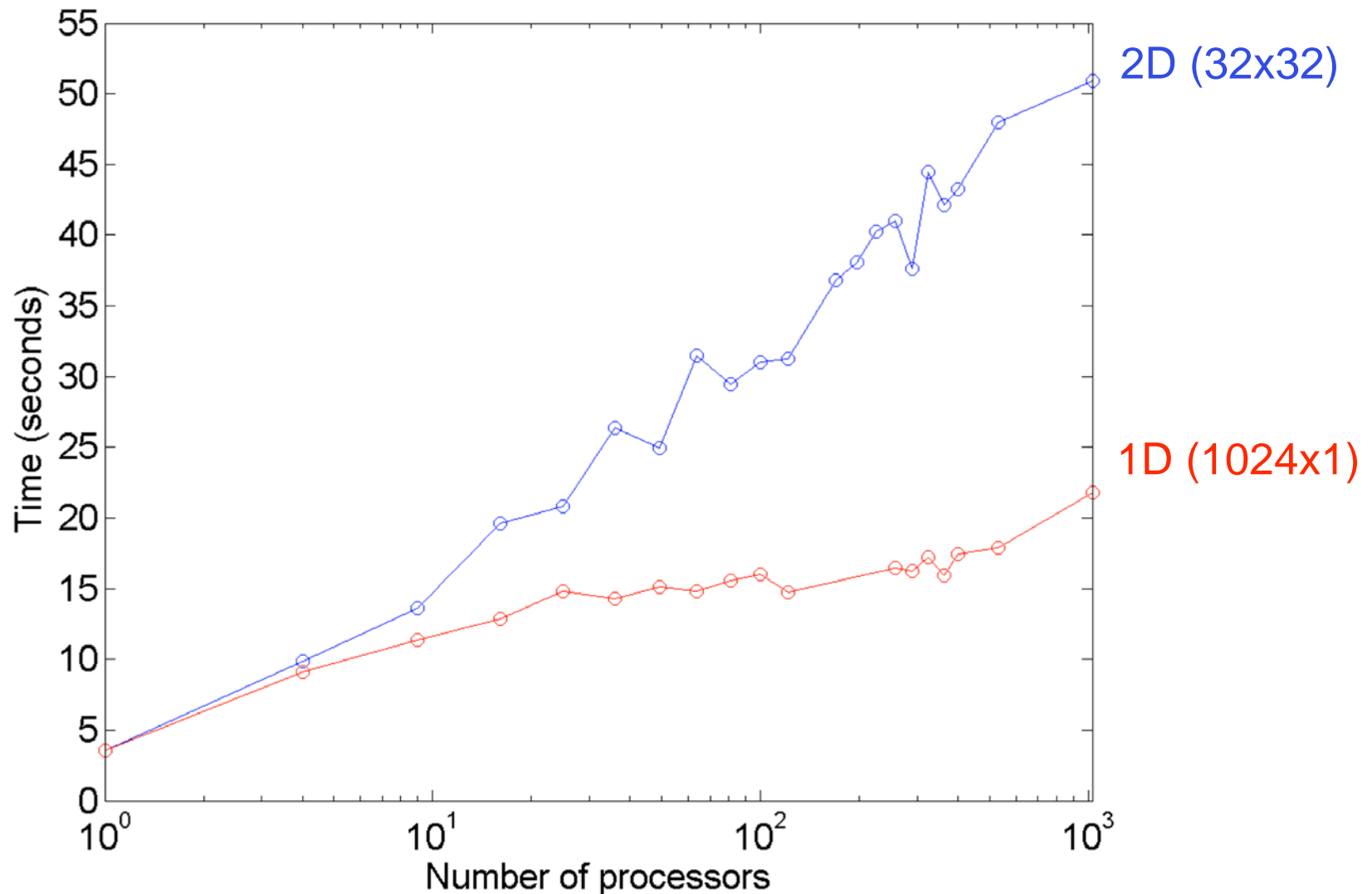
Parallel Search Experimental Setup

- Parallel Breadth First Search (BFS) algorithm
 - Level-synchronized algorithm
 - Report average time for 100 pairs
 - Does not take into account increasing graph avg. path length (varies from 5 to 9)
- Input graphs
 - Undirected Poisson random graphs with degree 10 or 100
 - Random 2D checkerboard partitioning
 - Vertices and edges accessed from memory
- Machines
 - MCR (Quadrics Linux Cluster)
 - BlueGene/L

Weak-Scaling, up to 1024 processors, $\langle k \rangle = 100$, 100 million vertices, 10 billion edges



Weak-Scaling, up to 1024 processors, $\langle k \rangle = 10$, 1 billion vertices, 10 billion edges

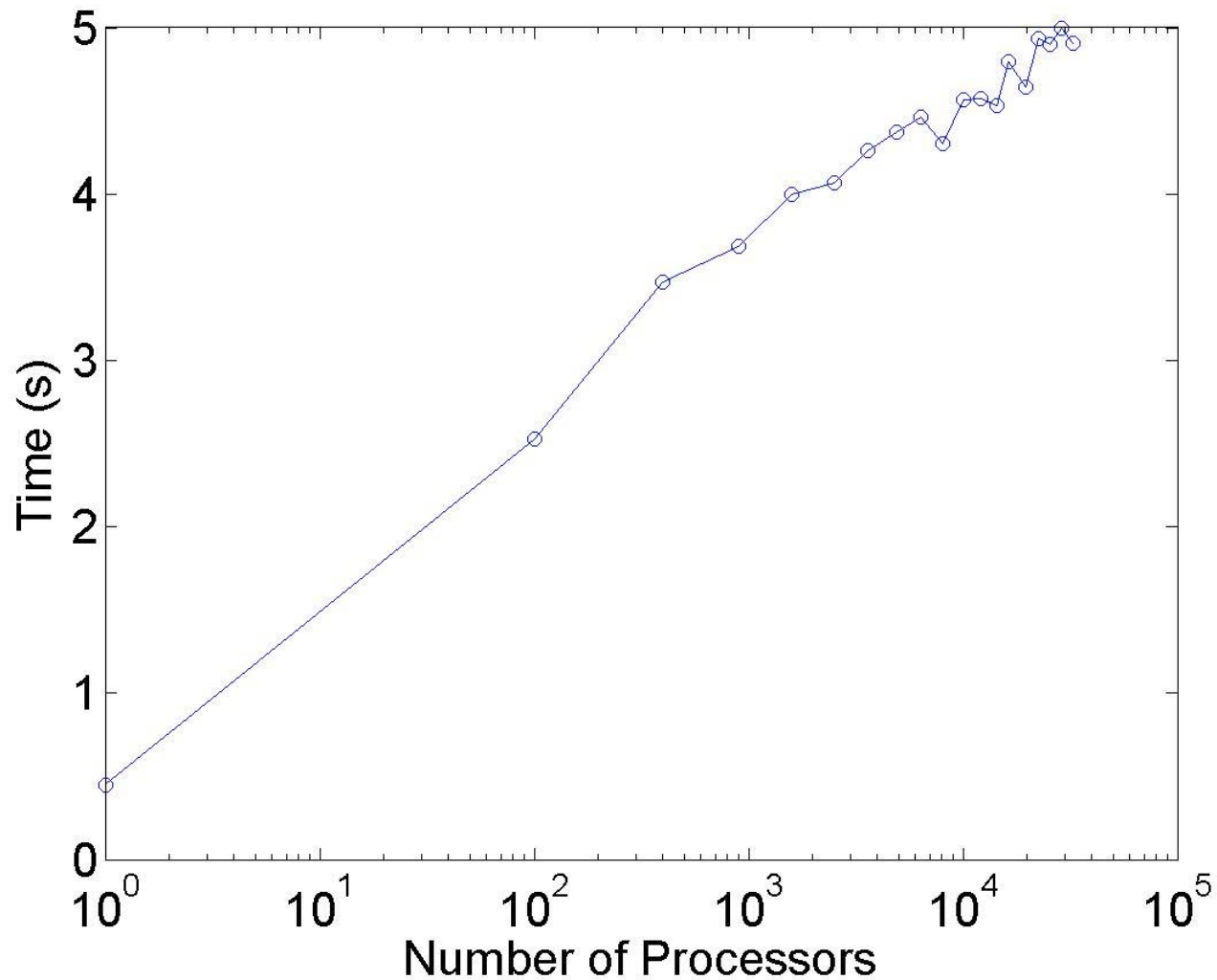


BlueGene/L timings, up to 32k processors

| Number of Vertices | Processor Mesh | Search Time (s) |
|--------------------|----------------|-----------------|
| 1.00 Billion | 100 x 100 | 4.37 |
| 1.96 Billion | 140 x 140 | 4.64 |
| 3.28 Billion | 181 x 181 | 4.90 |

Constant local problem size of 100k vertices/processor for a random graph with average degree 10.

Scalability on BlueGene/L up to 32k processors





Conclusions

- Heuristic search can be used to reduce the cost of relationship detection
- 2-D partitioning is effective for unstructured graphs with high average degree
- For more information:
<http://www.llnl.gov/casc/compnets>



Project Team and Collaborators

- Edmond Chow
- Tina Eliassi-Rad
- Keith Henderson
- Andy Yoo

- Bruce Hendrickson and William McLendon (Sandia Natl Labs)
- Umit Catalyurek and Doruk Bozdag (Ohio State University)

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